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Using SOM to Specify Mean Square Error and Standard Deviation Error for Non-Invasive Blood Pressure Measurement

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ABSTRACT

The measurements of blood pressure techniques are based on measuring the pressure of the cuff and on sensing the variation of the amplitude of pulsatile. Patient movement is sensitively effected by these measurements. The movements that are slightest unexpected could offset the readings of the automatic blood pressure meter by a large amount or render the readings totally meaningless. In this paper, windkessel models (two, three and four) were applied to generate blood pressure measurement. Blood pressure measurement for healthy person varies in the range 80mmHg/120mmHg. Windkessel models are mainly used to describe the load faced by the heart in pumping blood through the pulmonary or systemic arterial system, and the relation between blood pressure and blood flow in the aorta or the pulmonary artery. Characterizing the pulmonary or systemic arterial load on the heart in terms of the parameters that arise in windkessel models, such as arterial compliance and peripheral resistance. Artificial neural network (ANN) is tools for pattern classification computational that have been the matter of research that is renewed. ANN uses several learning algorithms and formats are being used in medical applications, industrial, and academic research ANN were also used in previous studies to estimate blood pressure. In this paper, self-organizing map (SOM) design have been used for determining mean square error (MSE) and standard deviation error (SD) for blood pressure (BP) measurement between inputs and outputs of training algorithm, where the input values in the neural network are the values estimated from windkessel models (two, three and four).

Keywords: Mean square error (MSE), Standard deviation error (SD), Artificial neural network (ANN), Self-organizing map (SOM), Blood pressure (BP), Systolic pressure (SP), Diastolic pressure (DP).

1. INTRODUCTION

Blood pressure is a very important measurement for estimation the health of human [1, 2]. Respectable analysis has been dedicated towards effective blood pressure measurement in many situations. Hence, a variety of methods are available for estimating and monitoring the pressure of blood. These methods can be classified as invasive and non-invasive. Invasive method involves in inserting blood pressure measuring cannula (thin flexible tubes) into the body [3] and making incisions. Non-invasive method involves some form of a cuff wrapped around a person's arm that is inflated and deflated while monitoring the pulse oscillations [4, 5, 6]. Non-invasive techniques are better because the painless nature is inherent and also have been automated to free up a doctor's attention for more significant tasks [6, 7]. In this paper, windkessel models (two, three and four) was designed to generate blood pressure measurement. The models of windkessel were created to describe the systemic arterial system and the heart as a hydraulic circuit in closed shape [8, 9]. Here, the circuit contained a pump of water connected to a chamber, filled with water except for a pocket of air. As it's pumped up, the water compresses the air that successively pushes the water out of the chamber. This analogy shows the mechanics of the heart. The values estimated from windkessel models are trained through SOM training algorithm. The SOM [15] is an unsupervised ANN which aims to discover some underlying structure in the data. The SOM is said to be topology preserving that has an explicit neighborhood function that preserves neighborhood relations of the neurons. One intuitive view of the SOM is that it extends classical vector quantization [16] by defining the neighborhood relations of the codebook vectors. However, this simple extension yields many useful properties. As results, the theory and applications of the SOM have been a topic of active research for about three decades. Neurons of the SOM are usually called map units or prototypes since they can be seen to be representative samples of the data (cf. codebook vectors in vector quantization). Each map unit is associated with a reference vector w_i and each data vector is mapped to a map unit whose reference vector is most similar to the data vector itself. The reference vectors mi are usually either emergently or explicitly weighted local

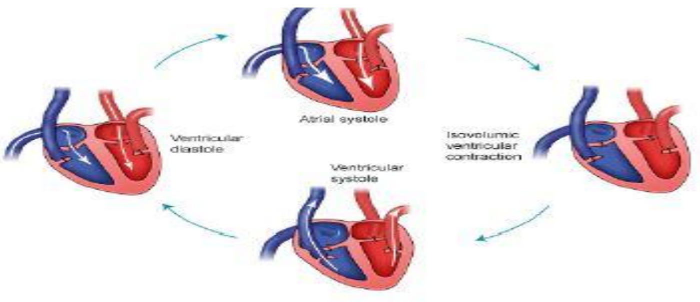
averages of the data associated with the given map unit in the original data space. The SOM is useful for making low dimensional, usually two dimensional, representations and visualizations of high dimensional data. It provides a topology preserving mapping from the original data space to the map units. If the map units are arranged to form a two dimensional lattice this provides means to visualize the data on a plane. A SOM type mapping has also been adapted to arbitrary data for which the mutual pairwise distances are defined [17]. The estimated blood pressure values from windkessel models are used as inputs through ANN training algorithm. MSE and SD were calculated between the inputs and outputs of ANN training algorithm.

2. MATERIALS AND METHODS

2.1. Blood pressure flow and windkessel model

The aorta is the largest artery within the human circulatory system, originating from the left ventricle of the heart and extending down to the abdominal cavity, where it branches into arteries that are smaller [10, 11]. The cycle of the cardiac is a closed loop, its system is pulsatile, and the heart flows blood throughout the system of the circulation in order to form a pulse wave as shown in (Figure 1).

Figure 1: Cardiac cycle form



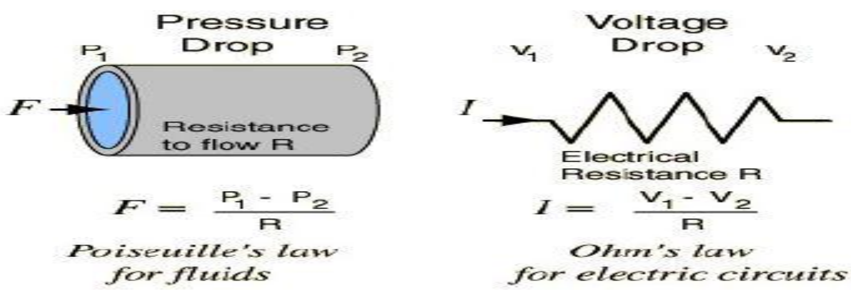
The first phase of the cardiac form, diastole of ventricular happens when the ventricles are relaxed and allow the oxygenated new blood to flow in from the atria [12]. The diastole of ventricular is followed by systole, where the ventricles contract and allow the blood to eject out to the body through the aorta. The pressure of blood rises when the ventricles contract and pump the blood into the aorta, at its maximum is named systolic pressure. At the beginning of following cardiac cycle, as the blood begins to flow into the ventricles, the pressure of the blood is at its lowest, and it is known as diastolic pressure [11]. The model of windkessel was created to describe the systemic arterial system and the heart as a hydraulic circuit in closed shape [8]. Here,

the circuit contained a pump of water connected to a chamber, filled with water except for a pocket of air. As it's pumped up, the water compresses the air that successively pushes the water out of the chamber. This analogy shows the mechanics of the heart. Windkessel models are used commonly to represent the undertaken load by the heart during the cardiac cycle. It connects blood pressure and blood flow inside the aorta, and distinguishes the compliance of the arterial, peripheral resistance of the valves and the inertia of the blood flow. The windkessel model takes the following parameters into consideration while modeling the cardiac cycle [13]:

- **Arterial compliance:** assign to the main artery extensibility during the cardiac cycle.
- **Peripheral resistance:** assign to the flow of resistance encountered by the blood as it flows through the systemic arterial system.
- **Inertia:** assign the blood inertia as it is cycled throughout the heart.

The windkessel is similar to the law of poiseuille's for a hydraulic system model. It characterizes the blood flow through the arteries as the flow of fluid through pipes. In this paper, we concentrate on the electrical circuit equivalent, as shown in (Figure 2).

Figure 2: Fluid dynamics and electrical circuit equivalents



2.1.1. Windkessel model description

Windkessel model suppose that:

- Cardiac cycle begins at systole.
- The systole period is 2/5th of the cardiac cycle period.
- Arterial compliance, peripheral resistance, and inertia are represented as a capacitor, a resistor, and an inductor respectively.

Windkessel models are explained in two different models as below [13, 14].

2.1.1.1. Two element windkessel model

The simplest model of windkessel, shows the hemodynamic state is the two element model. While a cardiac cycle, it takes into consideration the effect of total peripheral resistance and arterial compliance [13].

Figure 3: Diagrammatic representation of ejection of blood from ventricular and arterial circulation

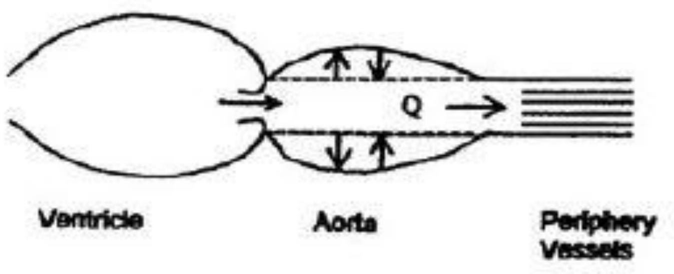
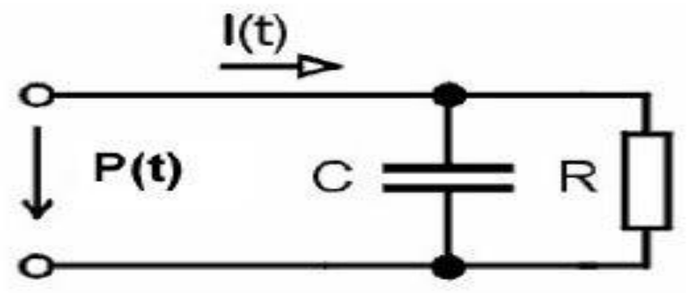


Figure 4: Electrical analog of the two element windkessel model



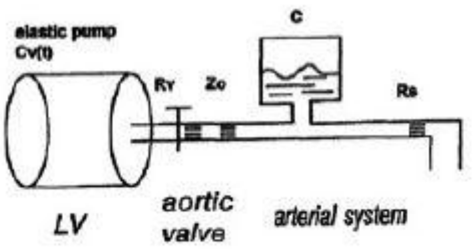
In the analog of the electrical, arterial compliance (C in cm^3/mmHg) is performed as a capacitor with properties of electric charge storage, the peripheral resistance of the arterial system (R in mmHg × s/cm^3) is performed as a resistor of energy dissipating. The blood flow from the heart (I(t) in cm^3/s) is similar to the flow of current in the circuit and the pressure of blood in the aorta (P(t) in mmHg) represents the variation of time electric potential. (Figure 4) shows that during systole state, the blood ejects from the ventricles to the aortic chamber compliant. The stored blood in the vessels of peripheral and the elastic recoil of aorta during diastole is seen as solid and dashed lines respectively. The electrical circuit analog of two element windkessel model is shown in (Figure 3) and the theoretical model of two element windkessel model is given as in (Equation 1).

$$I(t) = \frac{P(t)}{R} + C\frac{dP(t)}{dt} \qquad (1)$$

2.1.1.2. Three element windkessel model

Three element windkessel model demonstrate the distinguish resistance of the proximal aorta [14]. A resistor is combined in the series to account for this resistance to the flow of blood due to the valve of the aortic. The existing parallel combination of resistor capacitor performs the total peripheral resistance and aortic compliance in the two element model as discussed before. A hydraulic equivalent of the three element model is shown in (Figure 5). Compliance of the aortic due to the variation of the pressure is seen by allowing a bottle to afford volume isolation. The tube geometry represents the distinctive aortic resistance. Resistance to flow is varied by fractional opening and closing of needle valve shown.

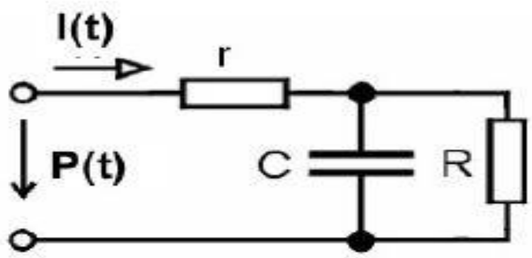
Figure 5: A hydraulic equivalent of the three element windkessel model



The electrical circuit analog of three element windkessel model is shown in (Figure 6) and the theoretical model for three element windkessel model is given as in (Equation 2).

$$\left(1 + \frac{r}{R}\right) i(t) + CR_1\frac{di(t)}{dt} = \frac{P(t)}{R} + C\frac{dP(t)}{dt} \qquad (2)$$

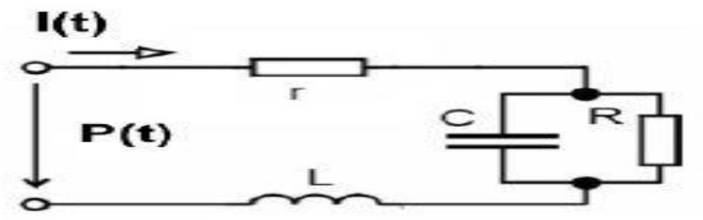
Figure 6: Electrical analog of the three element windkessel model



2.1.1.3. Four element windkessel model

This model contains an inductor in the main branch of the circuit as it accounts for the inertia to blood flow in the hydrodynamic model. The drop in electrical potential across the inductor is given as $L(di(t)/dt)$. The four element model gives a more accurate representation of the blood pressure vs. cardiac cycle time curve when compared to the two and the three element models. The electrical analog is shown in (Figure 7).

Figure 7: Electrical analog of the four element windkessel model



The theoretical modeling of four element windkessel model is given as in (Equation 3).

$$\left(1+\frac{r}{R}\right)i(t)+\left(rC+\frac{L}{R}\right)\frac{di(t)}{dt}+LC\frac{d^2i(t)}{dt^2}=\frac{P(t)}{R}+C\frac{dP(t)}{dt} \quad (3)$$

2.1.2. Mathematical model for windkessel models

The blood flow in the aorta from the ventricle during the cycle of cardiac is represented as $I(t)$ in our model. $I(t)$ is represented as a sine wave with amplitude I_0 during systole and is zero otherwise. This follows our learning of the cardiac physiology. At diastole, where the ventricles are restful, there is no flow of blood into the aorta, and then, $I(t) = 0$. However with ventricular contract during the systole, the flow of blood is ejected into the aorta and can be modeled as a sinusoidal wave, therefore the blood flow is calculated by (Equation 4).

$$I(t)=I_0\sin\left(\pi*\frac{\mathrm{mod}(t,T_c)}{T_s}\right) \quad (4)$$

Where t is time in seconds, T_c is the period of the cardiac cycle in seconds, T_s is the systolic period, in seconds, and $\mathrm{mod}(t, T_c)$ represents the remainder of t divided by T_c. T_s is assumed to be 2/5 T_c, according to the cardiac cycle dynamics. According to literature, the flow of blood in one cardiac cycle is 90 cm^3. We use that information to get the constant I_0 as shown in (Equation 5).

$$90 = \int_{0}^{T_c} I_0 \sin\left(\pi * \frac{\mathrm{mod}(t, T_c)}{T_s}\right) dt$$

$$I_0 = \int_0^{T_c} (1/90) \sin\left(\pi * \frac{\mathrm{mod}(t,T_c)}{T_s}\right) dt \tag{5}$$

$$I_0 = 424.1 \text{ mL}$$

Therefore the maximum amplitude of the blood flow during systole is $I_0 = 424.1$ mL. We solve analytically for the windkessel model that is given by (Equation 6).

$$C\frac{dP(t)}{dt} + \frac{P(t)}{R} = I(t) \tag{6}$$

Systolic Phase: inhomogeneous solution

$$\frac{dP(t)}{dt} + \frac{P(t)}{CR} = I(t) \tag{7}$$

Using the integrating factor: $u(t) = \int \frac{1}{CR} dt = e^{\frac{t}{RC}}$ we get (Equation 8).

$$\frac{dP(t)}{dt} e^{\frac{t}{RC}} + e^{\frac{t}{RC}} \frac{P(t)}{CR} = \frac{I_0}{C} \sin(\pi t/T_s)^{e^{\frac{t}{RC}}} \tag{8}$$

Note that:

$$\frac{dP(t)}{dt} e^{\frac{t}{RC}} + e^{\frac{t}{RC}} \frac{P(t)}{CR} = \frac{d}{dt}\left(e^{\frac{t}{RC}} P(t)\right)$$

So now we integrate the both sides to get (Equation 9).

$$\int d\left(e^{\frac{t}{RC}} P(t)\right) = \int \frac{I_0}{C} \sin(\pi t/T_s)^{e^{\frac{t}{RC}}} dt \tag{9}$$

And our solution is given by (Equation 10).

$$y(t) = c_1 e^{\frac{-t}{RC}} + \frac{-e^{\frac{t}{RC}} T_s I_0 R \left(C\pi R \cos\left(\frac{\pi t}{T_s}\right) - T_s \sin\left(\frac{\pi t}{T_s}\right)\right)}{{T_s}^2 + C^2 \pi^2 R^2} \tag{10}$$

To solve for the constant c_1, we consider the initial conditions for $P(t)$ at the start of the systolic cycle. As each systolic cycle is preceded by a diastolic cycle. At time t_{ss} = start of systolic cycle, $P(t)$ equals the diastolic pressure P_{ss}. Therefore c_1 is given by (Equation 11).

$$c_1 = P_{ss} + \frac{I_0 T_s R \left[C\pi R \cos\left(\frac{\pi(t - t_{ss})}{T_s}\right) - T_s \sin\left(\frac{\pi(t - t_{ss})}{T_s}\right)\right]}{{T_s}^2 + C^2 * \pi^2 * R^2} e^{\frac{(t - t_{ss})}{RC}} \tag{11}$$

Which gives us (Equation 12).

Diastolic phase: homogeneous solution

$$c_1 = P_{ss} + \frac{I_0 T_s R[C\pi R]}{{T_s}^2 + C^2 * \pi^2 * R^2} \tag{12}$$

$$C\frac{dP(t)}{dt} + \frac{P(t)}{R} = 0 \tag{13}$$

$$P(t) = ce^{\frac{-t}{RC}} \tag{14}$$

To determine the constant c, we solve for the initial condition for $P(t)$ at the start of diastolic cycle. At time t_{sd}= start of diastolic cycle, $P(t)$equals the diastolic pressure (p_{sd}). As each diastole is preceded by a systole, this is the pressure at the end of the systolic cycle. For all our analytical and numerical analysis, $p_{sd}$was determined from the solution of the preceding systolic cycle. We expect this number to be around 120 mmHg. This is because the blood pressure for a healthy person is around 120mmHg/80mmHg (systolic/diastolic). Given that we started with 80mmHg as our diastolic blood pressure, our model should be able to output the systolic blood pressure as 120mmHg. However, it should be noted that the diastolic blood pressure of 80mmHg was supplied as an initial condition only for the first cycle. For the remaining cycles, the blood pressure at the end of the preceding diastolic cycle was taken as the initial condition.

2.2. Statistical analysis and classification

2.2.1. Self-organizing map (SOM)

In clustering net, there are as many input units as an input vector components [18, 19]. Since each output unit represents a cluster, the number of output units will limit the number of clusters that can be formed. The weight vector for an output unit in a clustering net is called exemplar or codebook vector for the input pattern, which the net has placed on that cluster. During training, the net determines the output unit that is the best match for the current input vector. The unit whose weight vector is closest to the input vector is allowed to learn [20].

There are two methods for determination of the winner unit:-

Method1: The method uses the squared euclidean distance between the input vector and the weight vector, and chooses the unit whose weight vector has the smallest euclidean distance from the input vector.

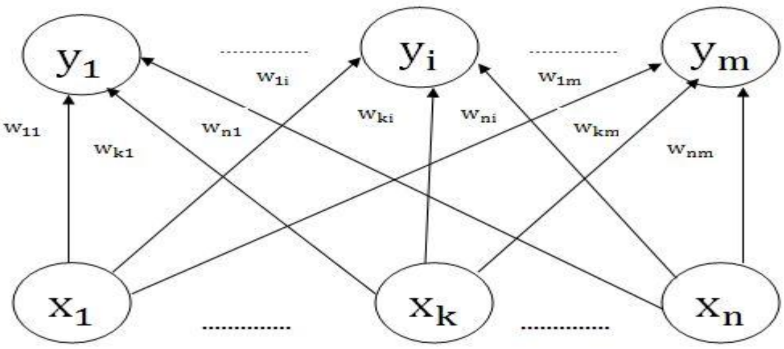
Method2: This method uses the dot product of the input vector and the weight vector. The dot product of an input vector with a given weight vector is the net input to the corresponding cluster unit. The largest dot product corresponds to the smallest angel between the input and weight vectors if they are both of unit length. SOM worked in the development of the theory of competition; as a result the competitive processing elements are referred to as kohonen unit. These SOM can also be termed as topology preserving maps. In a topology preserving map, the units located physically next to each other will respond to classes of input vectors that are likewise located next to each other. Although, it is easy to determine which classes of vectors are next to each other in a high dimensional space. Large dimensional input vectors are, in a sense, projected down on the two dimensional map in a way that maintains the natural order of the input vectors. The dimensional reduction could allow us to visualize easily important relationships among the data that otherwise might go unnoticed. The SOM, developed by kohonen, groups the input data into clusters which are, commonly used for unsupervised learning. In the SOM, all the units in the neighborhood that receive positive feedback from the winning unit participate in the learning process. Even if a neighboring unit's weight is orthogonal to the input vector its weight vector will still change in response to the input vector.

The simple addition to the competitive process is sufficient to account for the order mapping. The topological structure property is observed in the brain, but is not found in any other ANN expect SOM. There are 'm' cluster units, arranged in a one or two dimensional array and the input signals are n-tuples. The weight vector for a cluster unit is the exemplar of the input patterns associated with that cluster. In self-organizing process, the cluster unit whose weight vector matches the input pattern closely is selected as the winner. The winning and the neighboring units update their weights. The neighboring units weights vectors are not close to the input pattern but differ to some extent. Hence, the connection weights do not multiply the signal sent from the input unit to the cluster unit.

2.2.1.1. Architecture of SOM

The architecture of SOM is shown in (Figure 8). The key principal for map formation is that the training should take place over an extended region of the network centered "n" the maximally active mode. Hence, the concept of “neighborhood” should be defined for the net. This may be fixed by the spatial region between nodes within the self-organizing layer.

Figure 8: Kohonen self-organizing map



2.2.1.2. Training algorithm

Initially, the weights and learning rate are set. The input vectors to be clustered are present to the network. Once the input vectors are given, based on initial weights, the winner unit is calculated either euclidean distance method or sum of products method. Based on the winner unit selection, the weights are updated for that particular winner unit using competitive learning rule. An epoch is said to be completed once all the input vectors are presented to the network. By updating the learning rate, several epochs of training may be performed. The training algorithm is given in the following steps:-

Step 1: Set topological neighborhood parameters, set learning rate, initialize weights.
Step 2: While stopping condition is false, do steps 3-9.
Step 3: For each input vector x, do steps 4-6.
Step 4: For each j, compute squared euclidean distance
$D(j) = \sum(w_{ij} - x_i)^2$ i =1 to n and j =1 to m.
Step 5: Find index j, when D(j) is minimum.
Step 6: For all units j, with the specified neighborhood of j, and for all i, update the weights.
$w_{ij(new)} = w_{ij(old)} + \alpha\,[x_i - w_{ij(old)}]$.
Step 7: Update the learning rate.
Step 8: Reduce the radius of topological neighborhood at specified times.
Step 9: Test the stopping creation.

3. RESULTS AND DISCUSSION

In this paper, for solving the problem of pattern classification SOM algorithm for training was used. Training algorithm that is effective and system behavior that is better understood are the merits of this sort of neural network. Selection of input parameters of the network and execution of neural network are very significant for determining MSE and SD between the inputs and outputs of the ANN training algorithm.

(Figures 9-11) shows the relationship between blood pressure and time for both inputs and outputs of the training algorithm using SOM algorithm using windkessel models (two, three and four).

Figure 9: Relationship between blood pressure and time for both inputs and outputs of the training algorithm using SOM algorithm using two element windkessel model

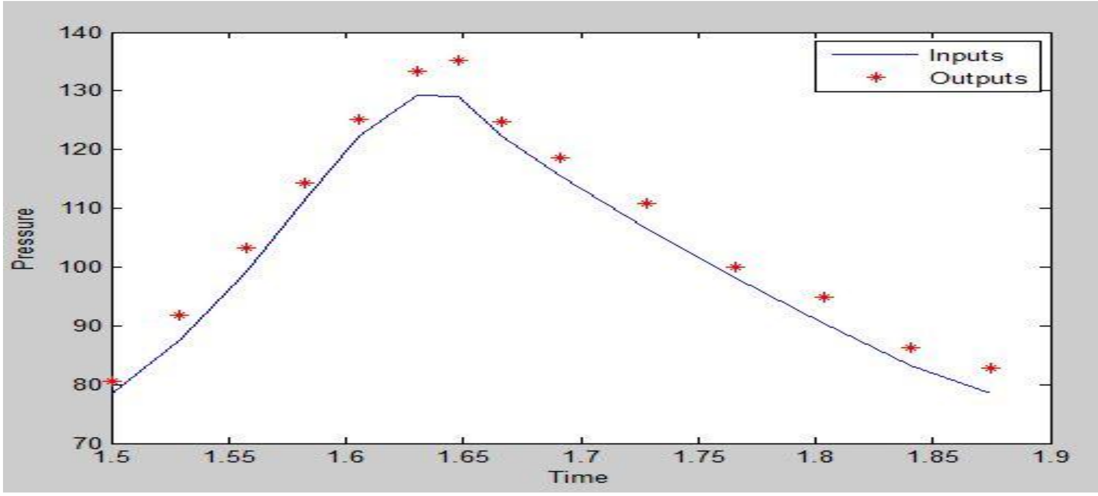


Figure 10: Relationship between blood pressure and time for both inputs and outputs of the training algorithm using SOM algorithm using three element windkessel model

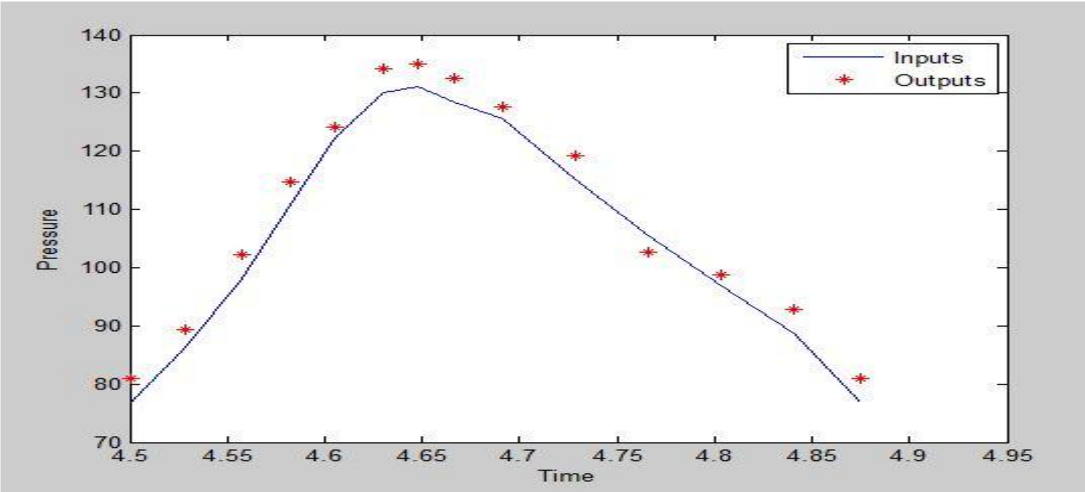
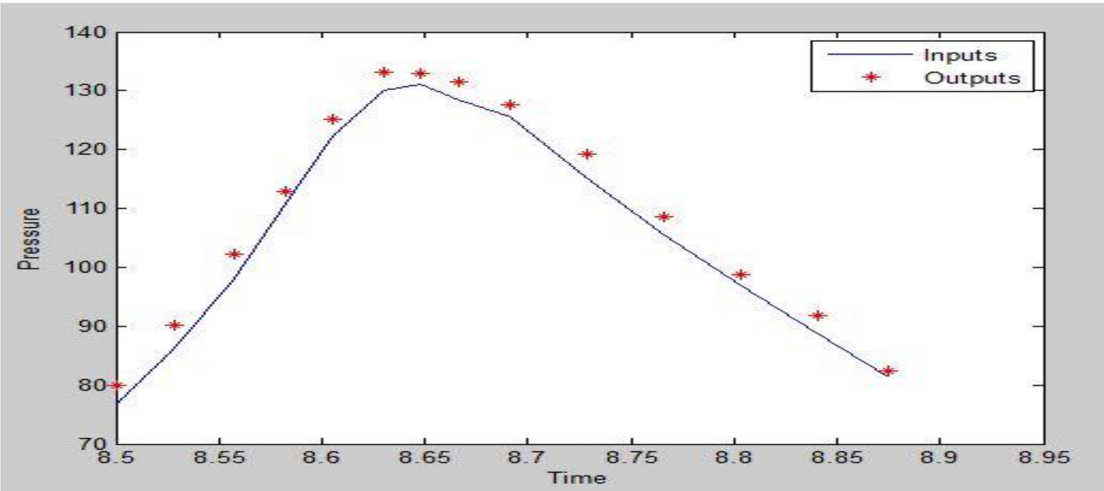


Figure 11: Relationship between blood pressure and time for both inputs and outputs of the training algorithm using SOM algorithm using four element windkessel model



(Table 1) shows the MSE and SD between blood pressure and time for both inputs and outputs of the training algorithm of SOM algorithm using windkessel models (two, three and four).

Table 1: Values of MSE and SD for both inputs and outputs of training algorithm of SOM using windkessel models

Windkessel models	**MSE**	**SD**
Two element windkessel model	0.1973	0.2324
Three element windkessel model	0.1870	0.1738
Four element windkessel model	0.1519	0.1821

4. CONCLUSION

In this paper, windkessel models (two, three and four) were applied to generate blood pressure measurement. Blood pressure for healthy person varies between 80mmHg/120mmHg. The estimated values from windkessel models (two, three and four) were applied and used as inputs for SOM training algorithm. MSE and SD were calculated between the inputs and outputs of SOM training algorithm.

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